Classification of OT Images of Arthritic Joints Using Spatial-Fourier Frequency Coefficients

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Abstract: Fourier Transform coefficients of absorption and scattering distributions, reconstructed from OT scans of proximal-interphalangeal joints, are used in conjunction with discriminate analysis to diagnose rheumatoid arthritis. Sensitivity and specificity of 91.0% and 90.0% were achieved, respectively.

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1. Introduction
Recent advances in hardware and software have increased the clinical utility of Optical Tomography (OT) as a tool for diagnosing and monitoring disease [1–3]. Our research group recently introduced data mining and machine-learning techniques to improve the ability to accurately and consistently diagnose rheumatoid arthritis (RA) from OT scans of proximal interphalangeal (PIP) joints [3]. In that study, transmission measurements across PIP joints were obtained using a frequency modulated near-infrared laser OT system. The transmission measurements, recorded by an intensified CCD camera, were used to reconstruct \( \mu_a \) and \( \mu'_s \) maps of tissue in and around the PIP joint. From that study it was evident that the optical properties in joints of subjects with RA are significantly different from optical properties in joints of subjects without RA. For example, inflammation of the joint increases \( \mu_a \) and \( \mu'_s \) of the synovial fluid and surrounding tissues. These changes can be observed in OT reconstructions.

Our group recently reported on the ability to classify PIP joints as affected or not affected with RA with 91% sensitivity and 86% specificity using linear discriminate analysis (LDA). Our general approach to image classification consisted of two steps. First, features were extracted from OT reconstruction (i.e. \( \mu_a \) and \( \mu'_s \) images, respectively) that included the maximum, minimum, variance, and ratio of maximum/minimum. Thus, each PIP joint was represented by 8 parameters (4 from \( \mu_a \) and 4 from \( \mu'_s \) reconstructions). Then, LDA was used to classify each image as affected or not affected using only the information contained in the 8-element vector.

This current work is motivated by the need to discover new image features that complement previous work in an effort to achieve even higher sensitivities and specificities, thus aiding in establishing OT as a viable clinical tool for the diagnosis of RA. We hypothesize that using spatial-distributions properties of the \( \mu_a \) and \( \mu'_s \) distributions will result in image features that meet these requirements.

However, the features used in previous work where all global values and they did not encode information regarding the spatial distribution of the optical properties [3]. In this work we overcome this weakness and explore the ability to classify PIP joints as affected or not affected with RA using features extracted from the three-dimensional Fourier transform of \( \mu_a \) and \( \mu'_s \) spatial distributions. These spatial Fourier transforms parameterize the spatial distribution of optical properties and reduced the dimensionality of the problem.

2. Methods
2.1. Clinical Data
Clinical data used in this study was collected from 33 subjects with RA and 20 healthy subjects. PIP joints II-IV were imaged from the dominant hand of subjects with RA, while PIP joints II-IV were imaged from both hands of subjects without RA. In total, 99 fingers were imaged from subjects with RA and 120 fingers from subjects without RA. A transillumination image was recorded for each joint (Fig. 1(a)). The surface geometry of each finger was computed and subsequently discretized using finite-volume elements (Fig. 1(b)). Maps of \( \mu_a \) and \( \mu'_s \) were recovered using the equation of radiative transfer as the light propagation model and a PDE-constrained technique as the optimization method [3,4].
Fig. 1: (a) Transillumination captured by a CCD camera during a scan of PIP joint II. (b) Discretized anatomical model of the PIP joint in (a), containing 7,424 nodes and 32,207 finite volume elements.

2.2. Feature Extraction

Maps of $\mu_a$ and $\mu'_a$ distributions were recovered for each PIP joint. Each map was subsequently converted into images of $\mu_a$ and $\mu'_a$ by converting the reconstruction data (defined on an unstructured mesh) to a structured grid. This step was necessary in order to perform advanced analysis on the data.

The image features of interest in this work were the Fourier transform coefficients of the $\mu_a$ and $\mu'_a$ images, computed using the Fast Fourier Transform (FFT). The FFT of each image ($N_1 \times N_2 \times N_3$ in dimension) was performed, resulting in and $N_1 \times N_2 \times N_3$ matrix of FFT complex coefficients. We truncated the matrix to store only an $n_1 \times n_2 \times n_3$ matrix of coefficients centered at $((N_1 + 1)/2, (N_2 + 1)/2, (N_3 + 1)/2)$, resulting in $n_1 \cdot n_2 \cdot n_3$ complex coefficients. As we were only interested in the absolute value of the coefficients, we were able to reduce the number of distinct coefficients to $(n_1 \cdot n_2 \cdot n_3 + 1)/2$ due to the symmetry properties of the FFT.

This allowed representation of each $\mu_a$ and $\mu'_a$ image by only $(n_1 \cdot n_2 \cdot n_3 + 1)/2$ real-valued coefficients instead of $N_1 \cdot N_2 \cdot N_3$ elements that defined the original reconstructed image. In this work $n_1 = n_2 = n_3 = 5$, resulting in 63 distinct real-valued coefficients. The coefficients are ordered from 1 to 63, ranked based on decreasing distance from the origin. This particular value was chosen because it was optimal in accurately representing the original image and simultaneously maintaining a low coefficient count (Figs. 2(a) and 2(b)). Each of the 63 coefficients was treated as an independent image feature.

2.3. Classification methods

A total of 126 features represented each imaged joint (63 from $\mu_a$ and $\mu'_a$, respectively). The area under the curve (AUC) from ROC analysis was used to quantify the classification strength of each individual feature. The features with the eight largest AUC values were selected for multidimensional classification.

Quadratic discriminate analysis (QDA) was used to determine the ability of multidimensional combinations of FFT coefficients to discriminate between PIP joints of subjects with RA and PIP joints of subjects without RA [5]. All possible combinations of the top 8 features were studied with QDA (ranging from 2-8 dimensional combinations). Classification strength was measured through sensitivity ($Se$) and specificity($Sp$), which are function of the number of true positives, true negatives, false positives, and false negatives returned by the classification system.

The leave-n-out ($n = 10.0\%$) cross validation method was used to test the classification ability of each feature combination. This strategy was executed 100 times for each feature combination, where a new random set of data was used during the training and testing phases, thus we avoided over-fitting the data. The results presented are the average sensitivities and specificities obtained over 100 distinct runs of the algorithms.

Fig. 2: (a) Original sagittal cross section through the middle of the PIP joint and (b) the approximate image captured by a three-dimensional discrete FFT (using only the first 5 frequencies). The original image contained 7,424 nodes and 32,207 finite volume elements, while equivalent information is captures using only 63 FFT coefficients.
3. Results

Table 1: Classification results from multi-dimensional combinations (standard error is $< 1.0\%$).

<table>
<thead>
<tr>
<th>Dimension</th>
<th>$Se$</th>
<th>$Sp$</th>
<th>$Y$</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>90.0%</td>
<td>81.0%</td>
<td>71.0%</td>
<td>(f:a:15, f:s:23)</td>
</tr>
<tr>
<td>3</td>
<td>92.0%</td>
<td>86.0%</td>
<td>78.0%</td>
<td>(f:a:6, f:a:27, f:s:23)</td>
</tr>
<tr>
<td>4</td>
<td>91.0%</td>
<td>90.0%</td>
<td>81.0%</td>
<td>(f:a:11, f:a:22, f:a:27, f:s:15)</td>
</tr>
<tr>
<td>5</td>
<td>90.0%</td>
<td>90.0%</td>
<td>80.0%</td>
<td>(f:a:6, f:a:11, f:a:31, f:a:39, f:s:23)</td>
</tr>
<tr>
<td>6</td>
<td>87.0%</td>
<td>91.0%</td>
<td>78.0%</td>
<td>(f:a:6, f:a:11, f:a:27, f:a:31, f:a:39, f:s:23)</td>
</tr>
<tr>
<td>7</td>
<td>87.0%</td>
<td>91.0%</td>
<td>78.0%</td>
<td>(f:a:6, f:a:11, f:a:22, f:a:27, f:a:39, f:s:15, f:s:23)</td>
</tr>
<tr>
<td>8</td>
<td>83.0%</td>
<td>90.0%</td>
<td>73.0%</td>
<td>(f:a:6, f:a:11, f:a:22, f:a:27, f:a:31, f:a:39, f:s:15, f:s:23)</td>
</tr>
</tbody>
</table>

Of the top eight features selected for classification, six were derived from FFT coefficients of $\mu$ images (6,11,22,27,31,39) and 2 from FFT coefficients of $\mu'$ images (15,23). The features are identified as $\mu_a$ or $\mu'_a$ coefficients by the preceding tag of “f:a” or “f:s,” respectively, followed the the FFT coefficient number.

The highest Youden index ($Y$) was 81.0%, corresponding to 91.0% sensitivity and 90.0% specificity, achieved with 4 dimensional classification using parameters {11,22,27} form $\mu_a$ and {15} from $\mu'_a$ (Table 1). It is important to note that 2-dimensional classification ($Se = 90.0\%, Sp = 81.0\%$) and 8-dimensional classification ($Se = 83.0\%, Sp = 90.0\%$) resulted in the lowest sensitivities and specificities. The classification performance increased with increasing dimension until it reached 4-dimensional combinations. Classification performance decreased at higher dimensions. This is important as it suggests that using too few features or too many features can result in poor classification results.

4. Conclusion and Discussion

The results presented in this study are evidence that spatial distribution information of $\mu_a$ and $\mu'_a$ images, as coded by the coefficients of the leading spatial-Fourier frequencies, can be used to efficiently classify OT images of PIP joints as affected or not affected by RA (91.0% sensitivity and 90.0% specificity). It is clear that the combination of features that yield optimal results is non-trivial, meaning that it is not low dimensional (one or two dimensional) or full dimensional (using all available features).

The results presented in this work are superior to results previously published (91.0% sensitivity and 86.0% specificity), however, the results are achieved with an independent set of image features. This is important, as it may be possible to combine features from both studies to achieve even higher sensitivities and specificities.

However, determining the optimal set of features by testing all possible feature combinations is possible only when the number of features is small (approximately $\leq 12$) as the number of possible combination increases exponentially with increasing number of features. Thus, identifying the optimal set of features from a large collection remains a challenge that is actively under investigation. The focus of our ongoing research is to explore the ability to diagnose RA using a combination of features presented in this work with the features presented in previous studies [3].

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References